November 4, 2014

Sequential decision making with human behavior modeling

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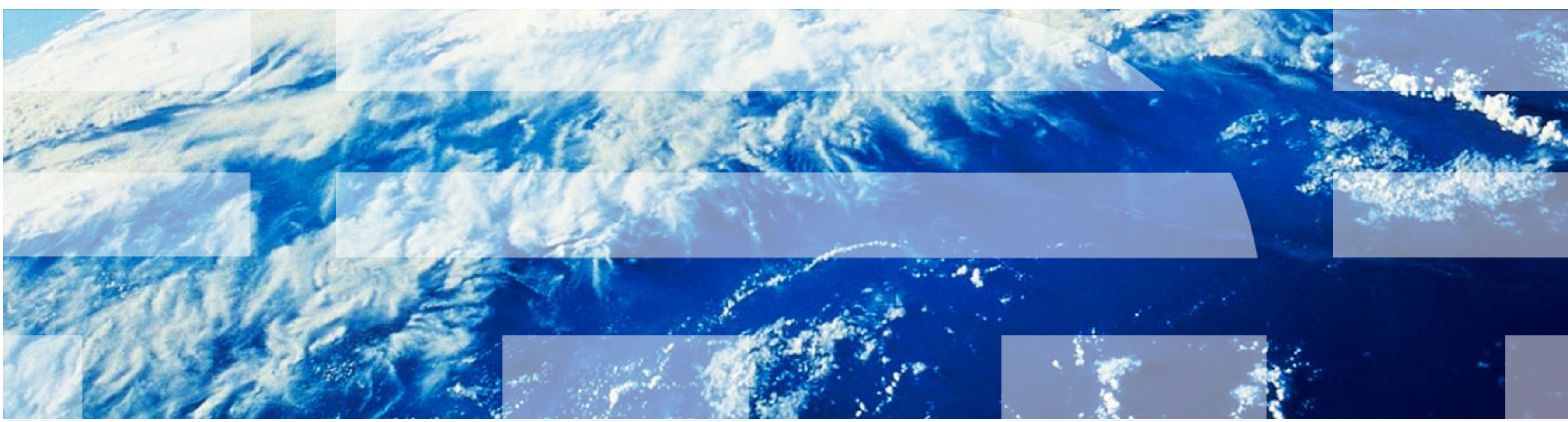
IBM Research – Tokyo



When mathematical science can help humans make better decisions

Too big data to use effectively
→ Machine Learning

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Too many candidates to find a solution
→ Optimization


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Too uncertain/random to be rational
→ This talk


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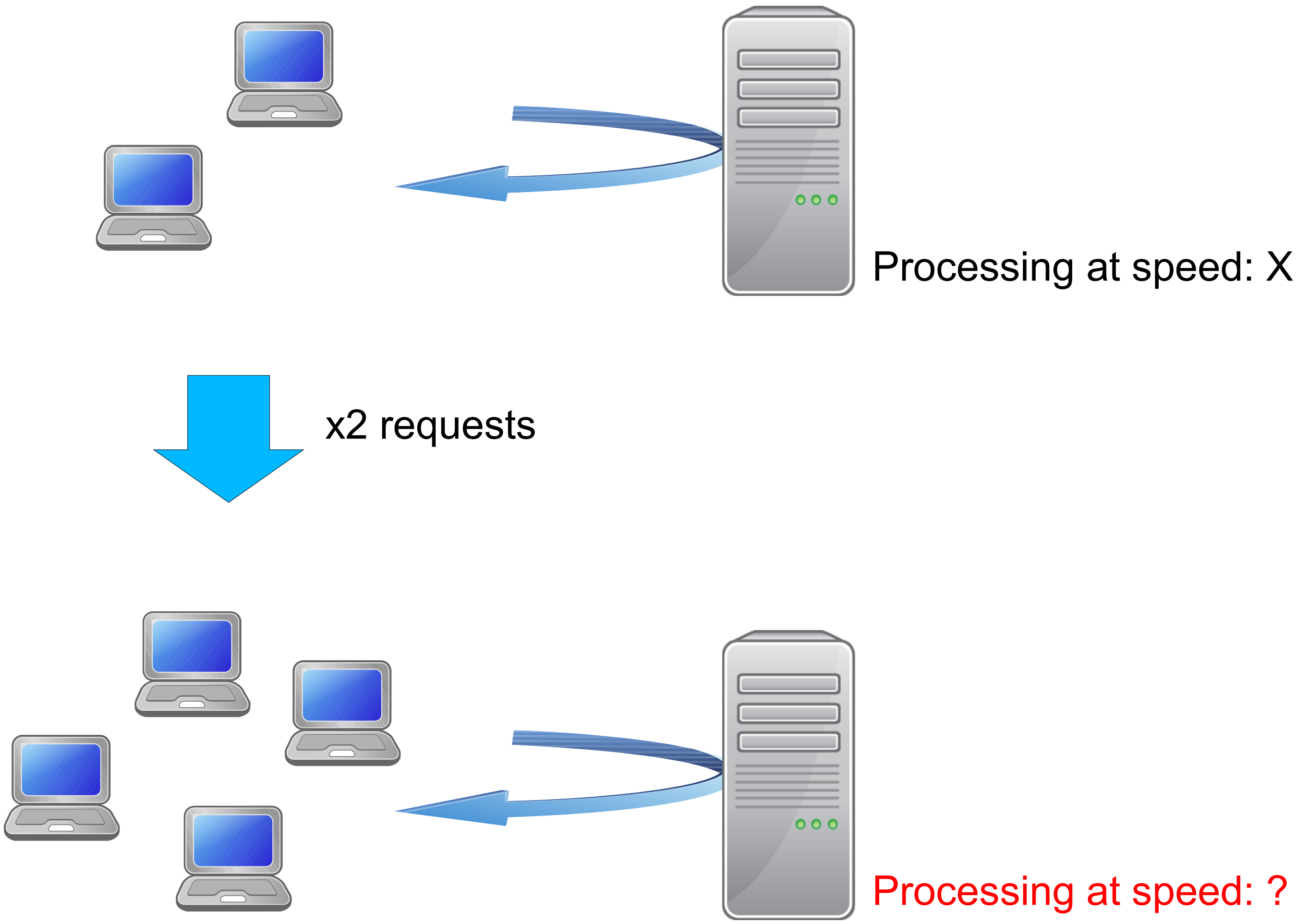
Human intuitions are often helpless under uncertainties

Example 1: How fast to serve to keep the average waiting time

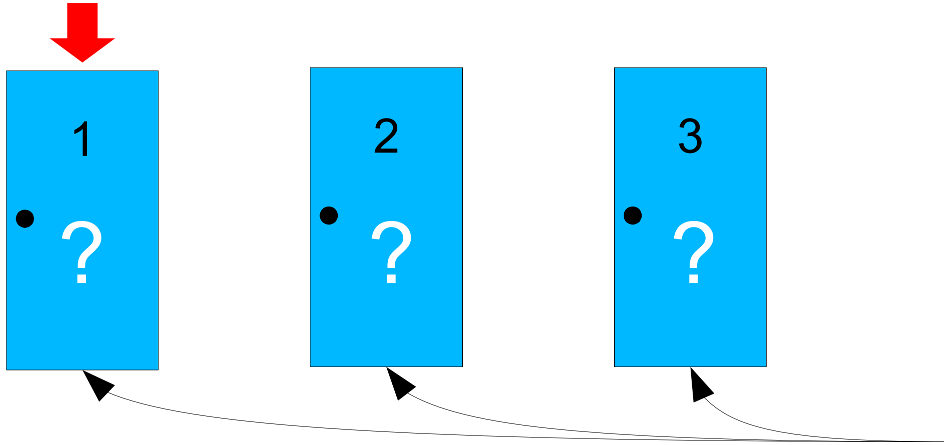


Processing speed: ×2

Average waiting time: ×1/2

Example 2: Monty Hall problem

1. You choose a door



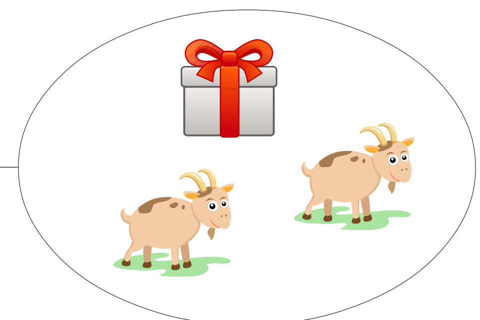
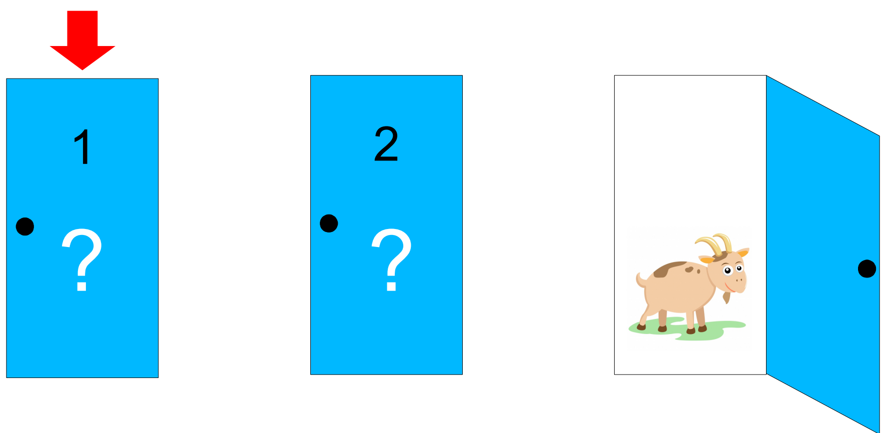


Image (goat) courtesy of AKARAKINGDOMS at FreeDigitalPhotos.net

2. I open one of the doors



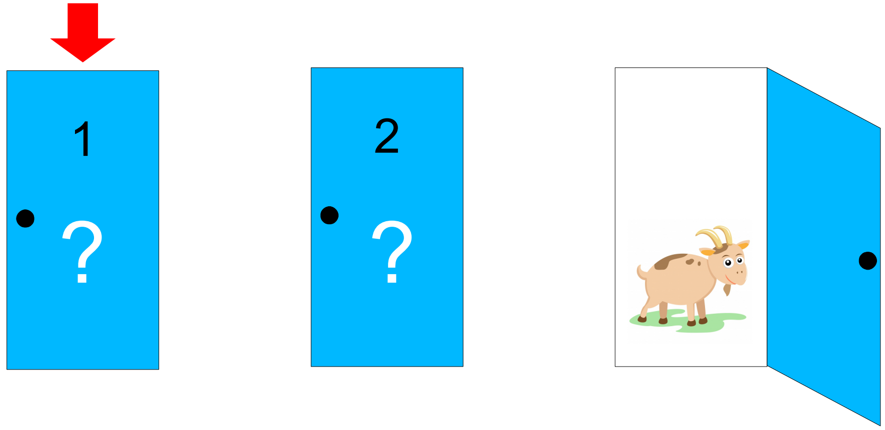
3. Would you change your choice?

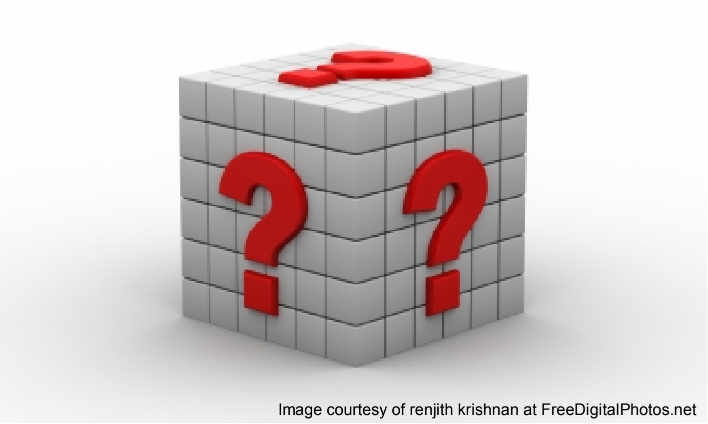
Humans are not good at making decisions under uncertainties

Under uncertainties,

- Making good decisions are hard for humans
  - even if we can examine all of the alternatives
  - even if we can examine all of the information

- Sequential decision making is particularly hard





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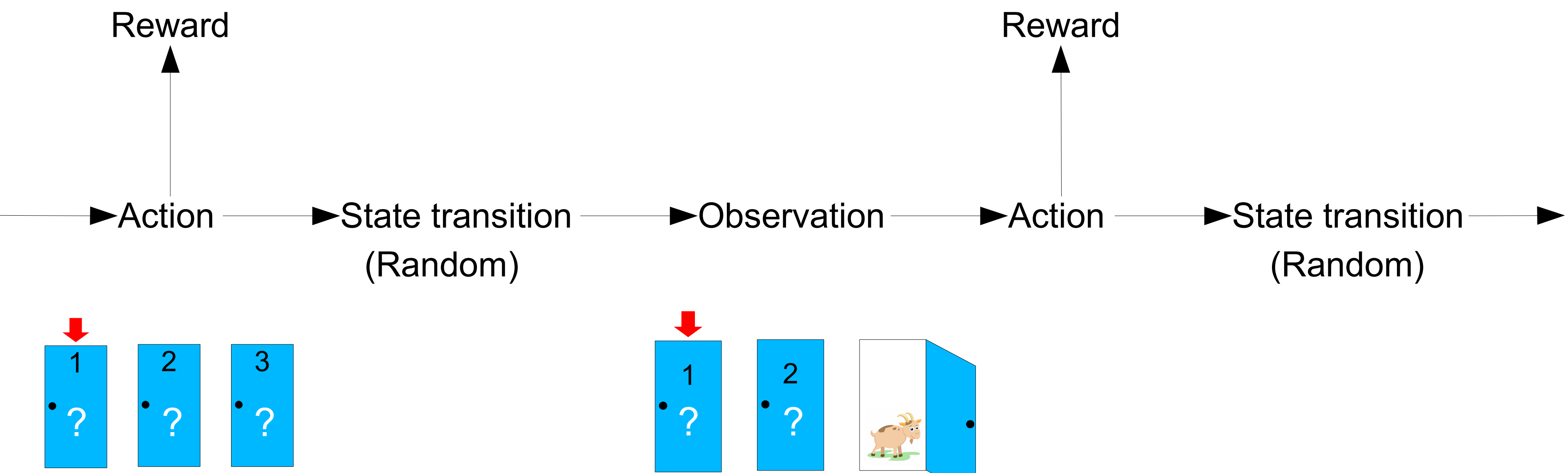
Sequential decision making: Acting for long term benefit



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Keep choosing good actions, depending on the state, to achieve a goal

Sequential decision making with humans in the loop

(under uncertainties)

Examples of sequential decision making with humans in the loop

Interaction with customers

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Recommendation
Information
Promotion

Purchase
Question
Request

Image courtesy of stockimages at FreeDigitalPhotos.net

Coffee tasting

Image courtesy of punsayaporn at FreeDigitalPhotos.net

- Blend
- Roast
- Grind

Feedback

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Education

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Advice
Lecture
Examination

Attend
Request
Question

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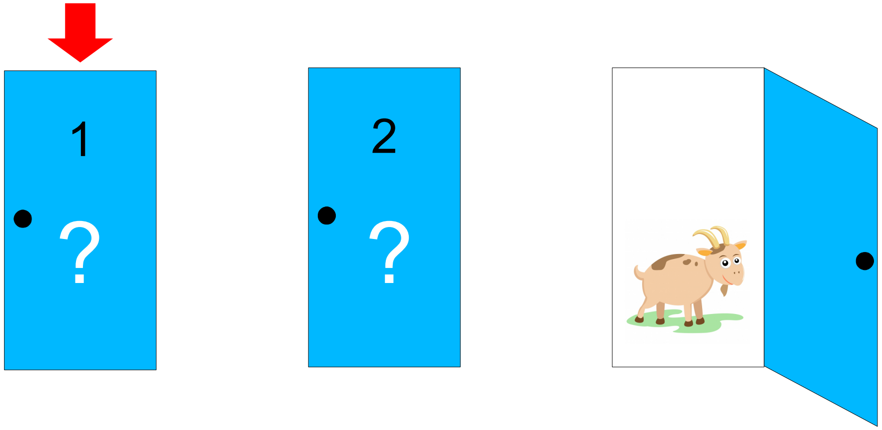
Recall

Humans are not good at making decisions under uncertainties

Under uncertainties,

- Making good decisions are hard for humans
  - even if we can examine all of the alternatives
  - even if we can examine all of the information

- Sequential decision making is particularly hard



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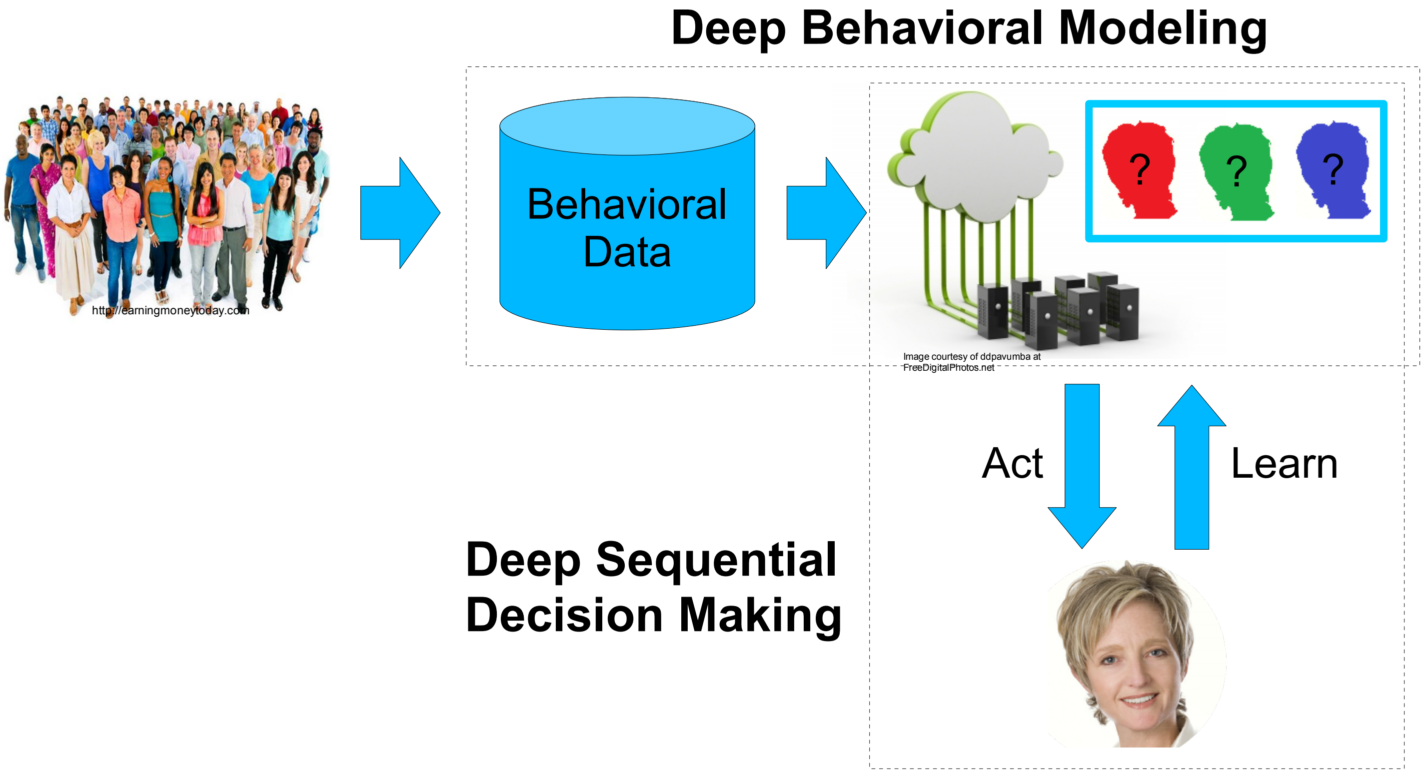
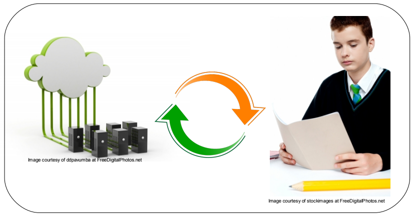
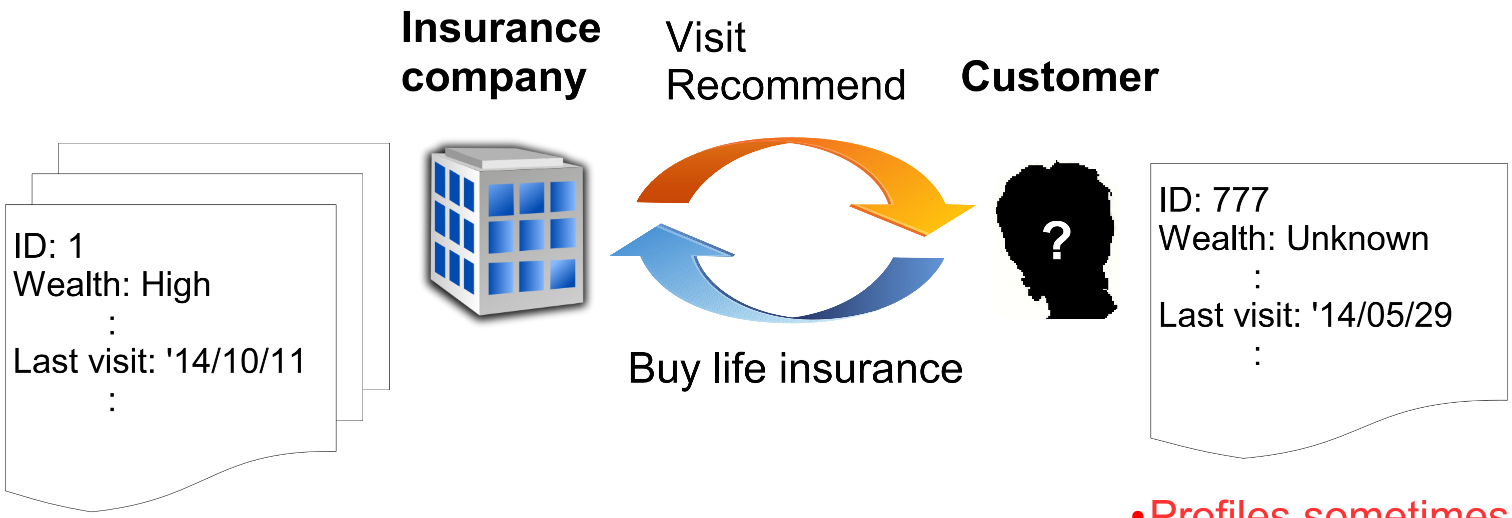
We improve the experience of customers by quickly learning the behavior of individuals and personalizing interactions





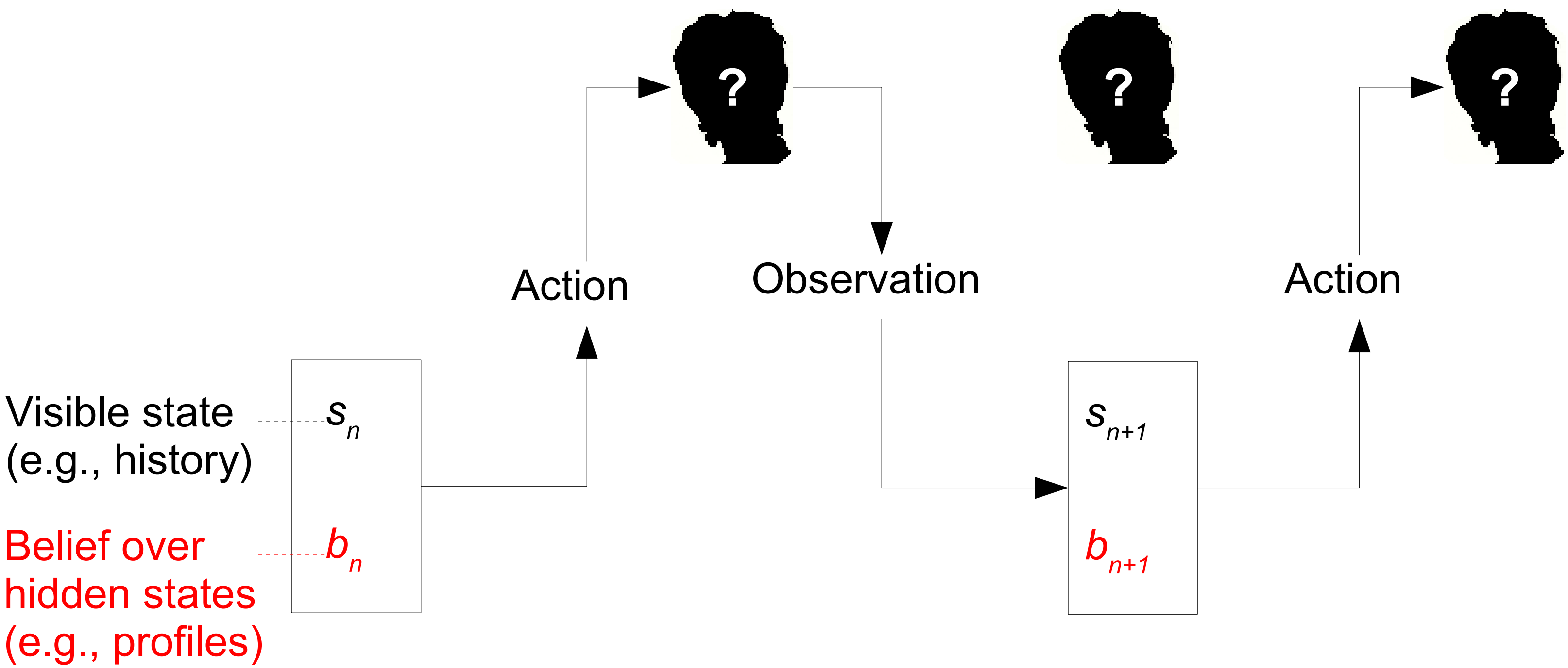
Example of deep sequential decision making: Estimating customers' profiles while maximizing the life time value of those customers



Profiles and historical data of many customers

- Profiles sometimes unknown
- Historical data usually known

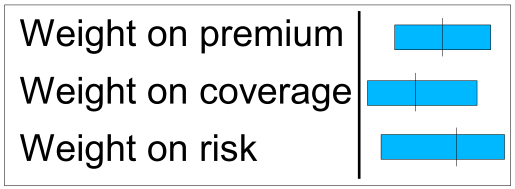
Our approach: Learning human behavior for personalized sequential decision making



Example of a belief state: *b* = (probability of low wealth, probability of high wealth)

Example 2: Preference elicitation of insurance customers

Initial estimate

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Choose the better

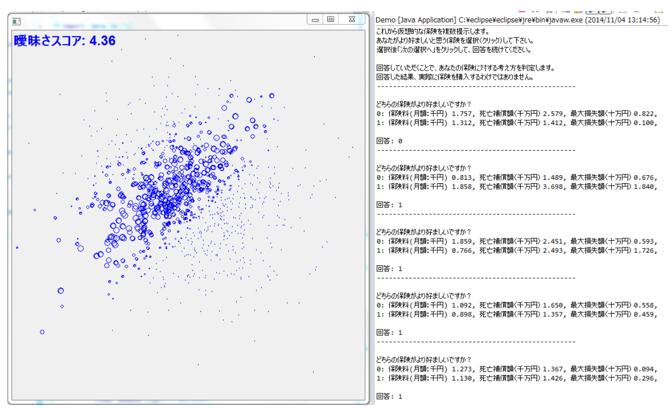
Insurance A ☐ | Insurance B ☐

Next

Deep sequential decision making for generating questions

- Maximizing the amount of information
- Minimizing customers' load

choice



Choose the better

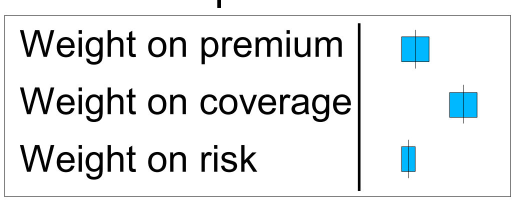
Insurance A ☐ | Insurance B ☐

Next

choice

:

Elicited preference

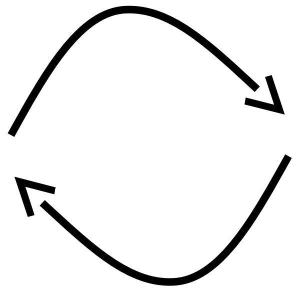


Example 3: Smart phones understanding users

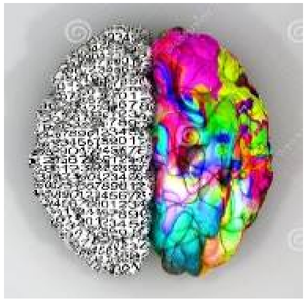
Novice user

Application

Operations



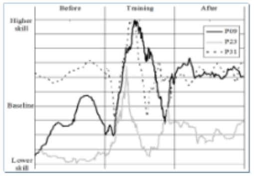
Assist



Smart Phone Assistent

Real time analysis

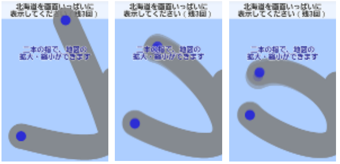
Estimate skills



Detect stumbles

Deep sequential decision making for selecting optimal method:

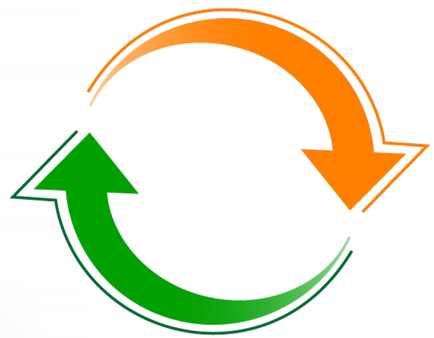
- Help
- Operation guide
- Game



Sumaho Dojo (KDDI R&D Laboratories)
https://play.google.com/store/apps/details?id=jp.kddilabs.eui.map

Good sequential decision making with humans in the loop relies on behavioral modeling

Image courtesy of ddpavumba at FreeDigitalPhotos.net



Behavior?
Decision?
Choice?

Deep choice modeling

Complex input
- How they look
- How they read

Complex human choice
- Attraction effect
- Compromise effect
- Similarity effect

Choice set

Choice

Images from amazon.co.jp

Example of attraction effect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Dan Ariely, *Predictably Irrational*, 2010

16 selected

0 selected

84 selected

Example of attraction effect

68 selected

32 selected

Dan Ariely, *Predictably Irrational*, 2010

Example of compromise effect

	A	B	C	D	E
CPU [MHz]	250	300	350	400	450
Memory [MB]	192	160	128	96	64
{A,B,C}	36	176	144		
{B,C,D}		56	177	115	
{C,D,E}			94	181	109

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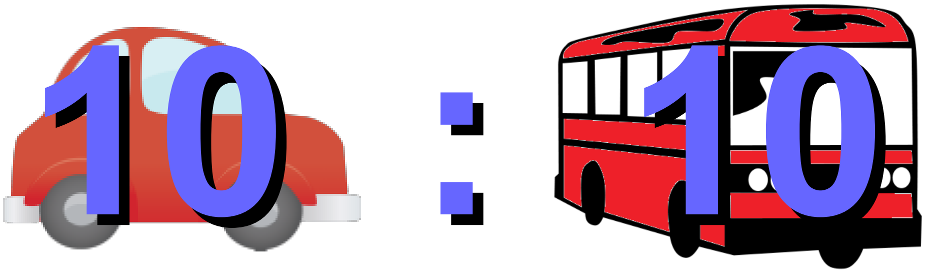
	A	B	C	D	E
Power [Watt]	50	75	100	125	150
Price [$]	100	130	160	190	200
{A,B,C}	45	135	145		
{B,C,D}		58	137	111	
{C,D,E}			95	155	91

Kivetz et al., “Alternative models for capturing the compromise effect,” *Journal of Marketing Research*, 2004.

Example of similarity effect

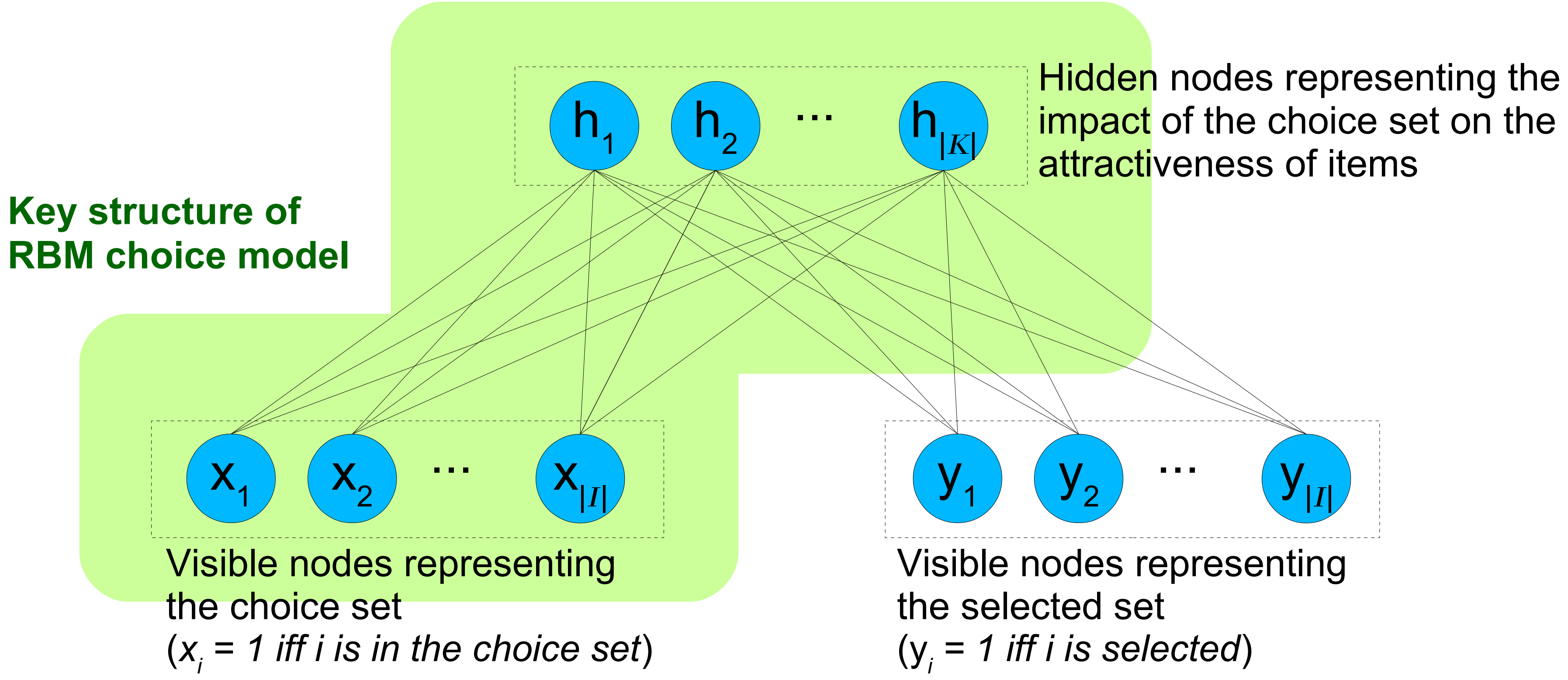
A traveler has the choice between a (red) car and a (red) bus



A blue bus is added to the option set

A new restricted Boltzmann machine (RBM) for modeling and learning typical phenomena of human choice

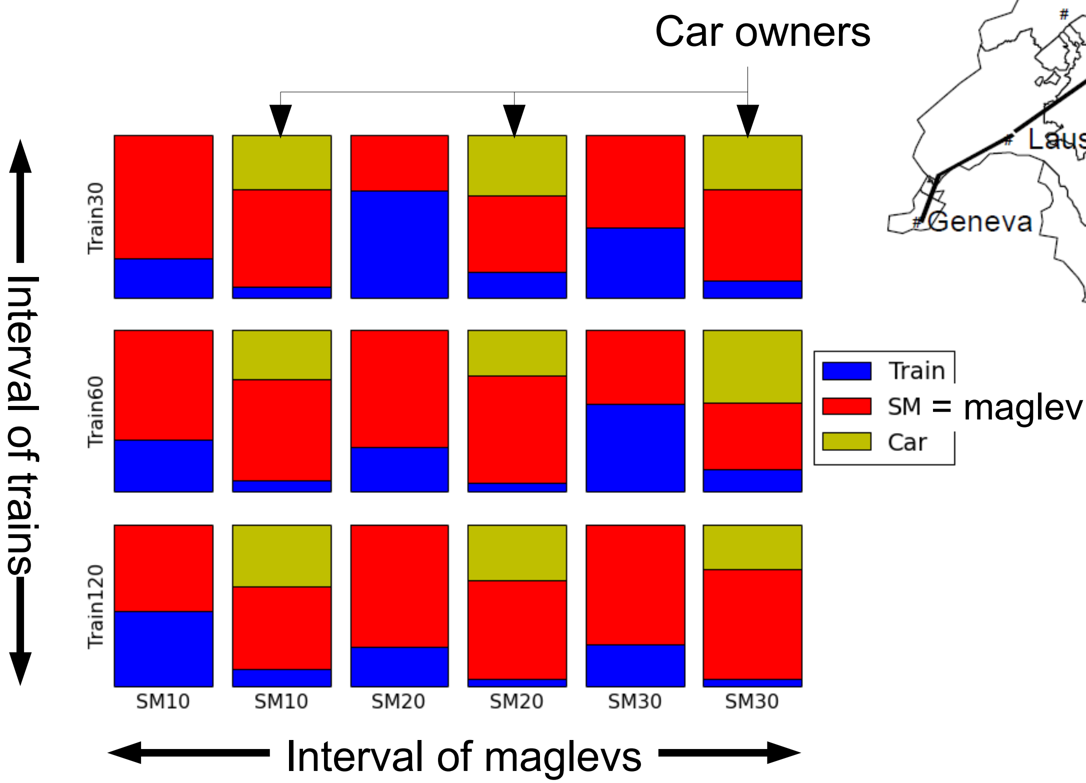
The first choice model that can
1. represent all of the three typical choice phenomena
2. be trained from data

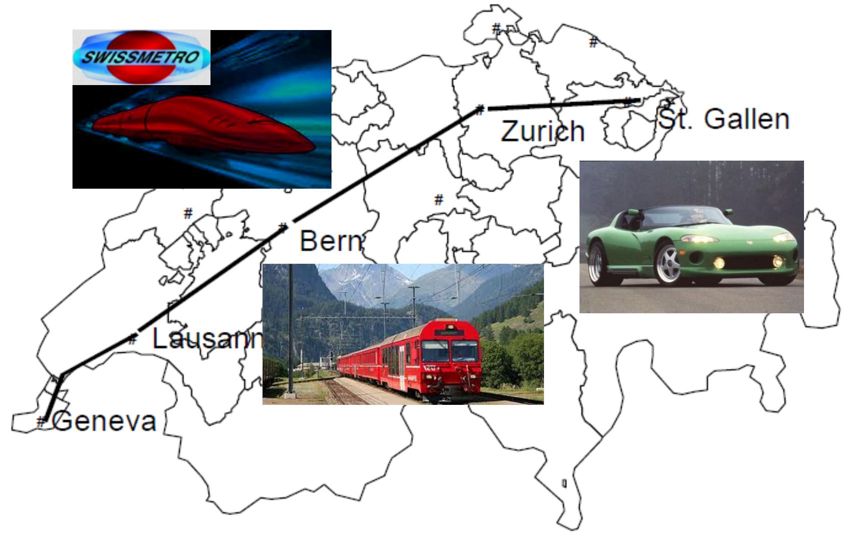


T. Osogami and M. Otsuka, "A restricted Boltzmann machine modeling human choice," to appear in NIPS 2014

Predicting human choice about transportation means: Maglevs, trains, or cars?

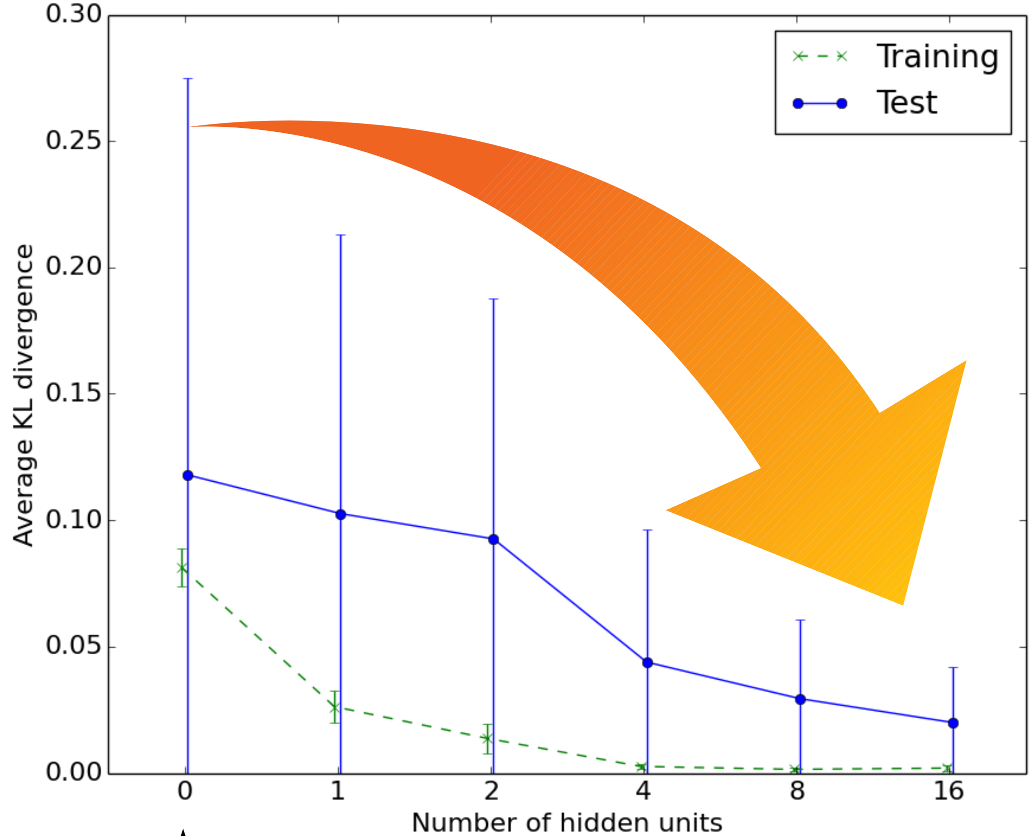
Relative attractiveness of maglevs and trains depends on the availability of cars





RBM choice model enables predicting human choice with high accuracy

Prediction error

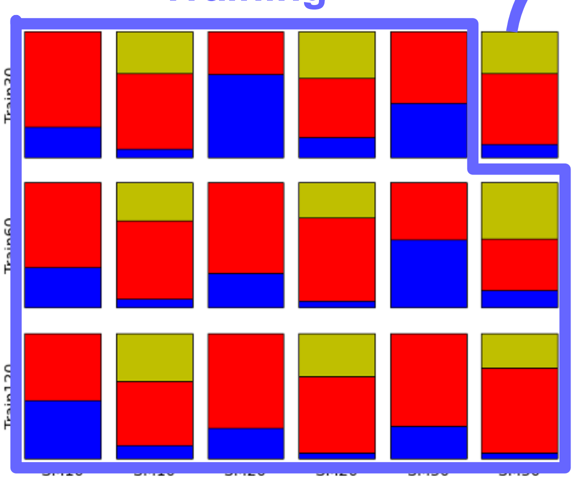


Multinomial logit model

RBM choice model

Training

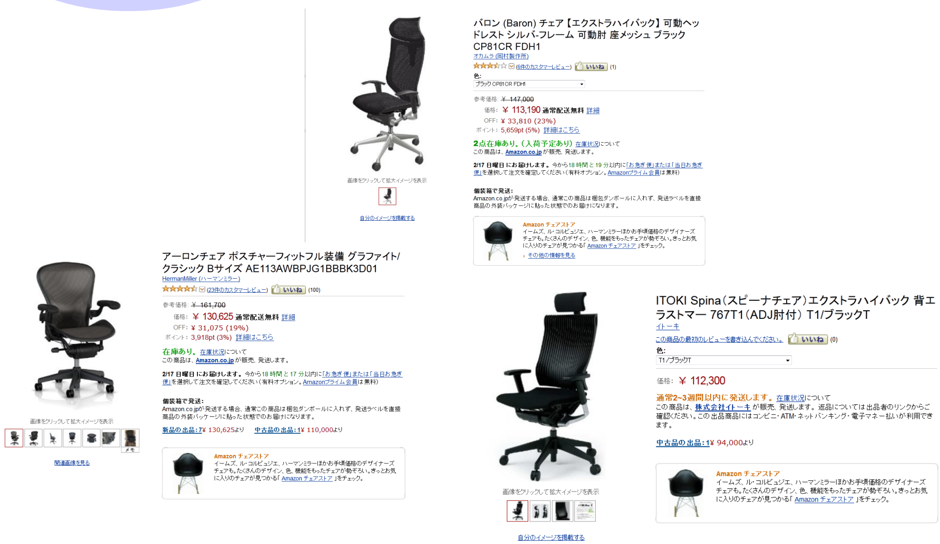
Test



Deep choice modeling

Complex input
- How they look
- How they read

Complex human choice
- Attraction effect
- Compromise effect
- Similarity effect

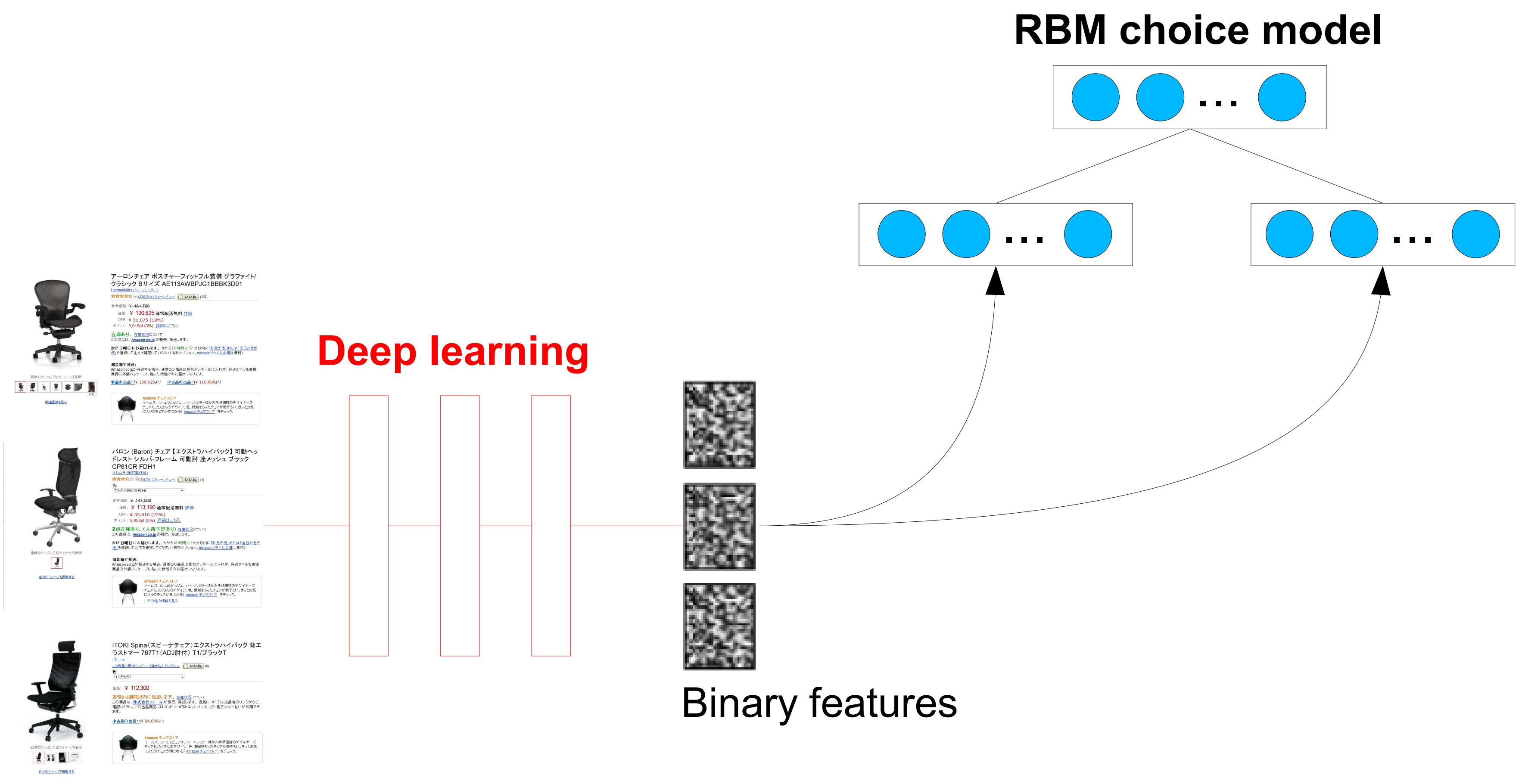


Choice set

Choice

Images from amazon.co.jp

Features extracted via deep learning can be used as input of RBM choice model



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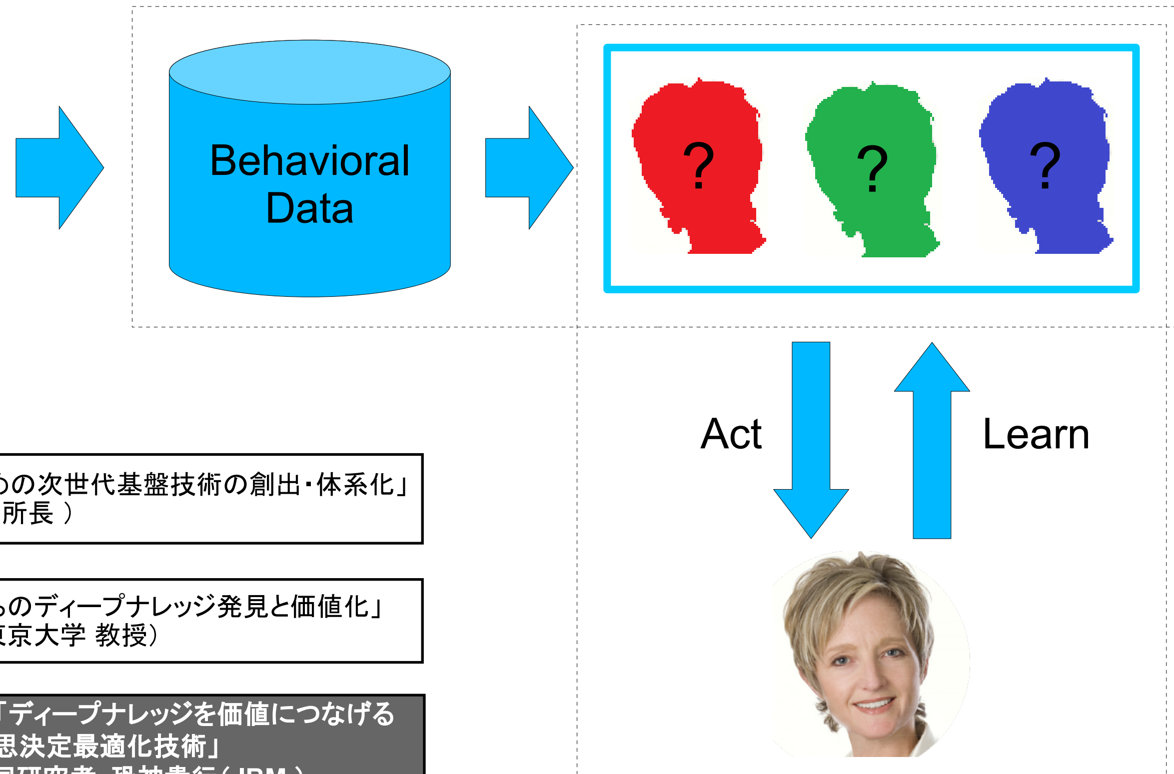
Deep Behavioral Modeling



Deep Sequential Decision Making

JST CREST

研究領域「ビッグデータ統合利活用のための次世代基盤技術の創出・体系化」
研究総括：喜連川優（国立情報学研究所 所長 ）

研究課題「複雑データからのディープナレッジ発見と価値化」
研究代表者：山西健司（東京大学 教授）

研究題目「ディープナレッジを価値につなげるための意思決定最適化技術」
主たる共同研究者：恐神貴行（ IBM ）